JOURNAL OF SCIENCE AND TECHNOLOGY
ISSN: 2229-8460 e-ISSN: 2600-7924

JST

Vol. 17 No. 2 (2025) 95-104
https://publisher.uthm.edu.my/ojs/index.php/jst

AI-Based Social Assistance for Children with Neuropsychiatric Disorders: Enhancing Social Behavior and Interaction

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DOI: https://doi.org/10.30880/jst.2025.17.02.008

Article Info

Received: 11 June 2025
Accepted: 7 November 2025
Available online: 30 December 2025

Keywords

Neuropsychiatric disorders, ADHD, autism, artificial intelligence, emotion recognition, pediatric therapy

Abstract

Children diagnoses with conditions such as ADHD or autism have difficulty with social interaction and managing emotions. These difficulties make traditional therapy inefficient. In this study, we will introduce artificial intelligence (AI) and see how it will support these children in developing better social skills. Hence, we present a tool called Spark Humanoid; an agent that uses AI to give kids feedback based on their facial expressions and how they respond during fun, and game session. The system uses convolutional neural network (CNNs) to understand the child's emotions and applies the A* algorithm in puzzle games to offer helpful hints and adjust difficulty as needed. We tested the tool during therapy sessions with support from the Palestine Childhood Institute. The system shows promising results, since kids seemed more engaged and responded more positively when using the AI tool compared to traditional sessions. These results shows that AI could be a useful addition to therapy, giving us new ways to help children with neuropsychiatric challenges.

1. Introduction

Neuropsychiatric disorders are conditions that affect a person's feelings, thoughts, and behavior by influencing both the neurological and psychological functions of the brain. Disorders like schizophrenia, bipolar disorder, anxiety, depression, ADHD, PTSD, and autism spectrum disorders are included in this category. These conditions can be caused by a variety of factors, including brain injuries, environmental factors, genetics, or a combination of these [1].

Due in large part to the ongoing conflict and the lingering effects of war-related trauma, ADHD is regarded as one of the most common disorders in Palestine. According to Al Jazeera News [2], about 59% of children in Gaza were found to have psychological problems after the war in 2014. A study from An-Najah National University in Nablus looked into this further by focusing on college students. Over 150 students were surveyed using 17 questions from the World Health Organization's Adult ADHD Self-Report Scale (ASRS) v1.1 [3]. The results showed that 30% of the students had signs of ADHD.

Even more worrying, 42% of the students said they had never even heard of ADHD. This shows there's a serious lack of awareness and a real need for better education about the condition.

These findings point to the urgent need for earlier diagnosis, proper treatment, and better public understanding of ADHD and mental health in general across Palestine. As shown in Figure 1, 59% of kids are reported to have mental health challenges, while 41% are not. This highlights how important it is to spread awareness and create strong support systems for children. Getting help early, along with the right care, can really make a big difference in their emotional and mental well-being.

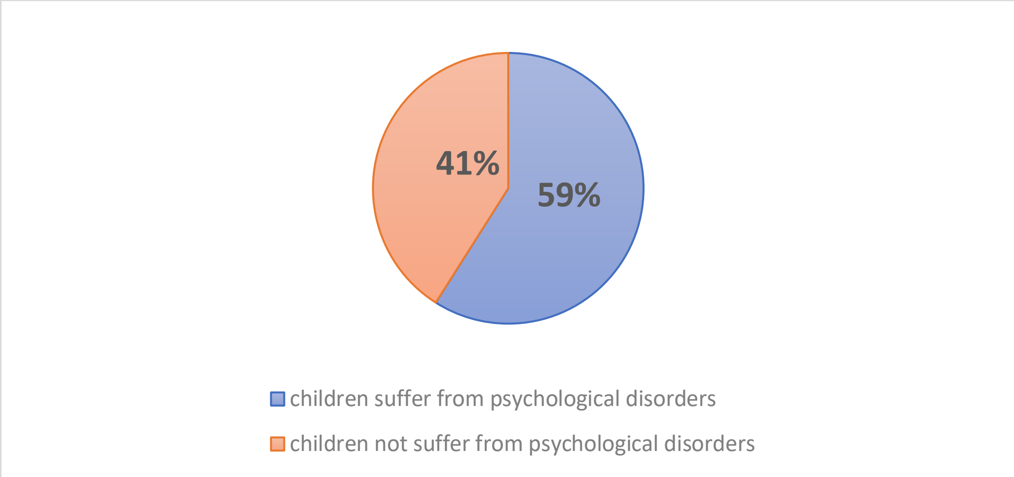

Fig. 1 *Prevalence of psychological disorders among children*

Attention Deficit Hyperactivity Disorder (ADHD) [4] is one of the most common behavioral conditions found in children. Developing effective support and intervention strategies requires a clear understanding of the sources of this behavior and how best to address it. Children with ADHD often face difficulties in regulating their emotions, which can make it harder for them to communicate and interact socially. Therapists working with these children may struggle to build strong connections, as the ways these kids express themselves (including changes in their tone of voice) can be quite different from what's typically expected. On top of that, traditional toys and activities often fail to capture their interest or hold their attention during therapy or playtime.

Artificial intelligence (AI) s plays a big role in mental health care. It offers tools that help with treat, manage, and understand different mental health conditions. By looking at medical records and psychological info, AI can support doctors and therapists in making better and more accurate diagnoses [5].

Moreover, these days, there are different AI apps and digital programs that help people deal with stress, anxiety, or depression [6]. They're easy to use and they offer support anywhere and anytime.

In addition, smart devices can track things like sleep, movement, and other daily habits. This kind of data gives doctors a clearer picture of someone's mental health, which helps them adjust care as needed [7].

Using AI to diagnose mental health conditions has a lot of promise. AI systems can go through patient info to spot early signs of things like anxiety or depression. Also, researchers are using machine learning to study brain scans, which can really help in figuring out different mental health issues [8]. On top of that, AI is being used in online therapy programs, many of them based on proven methods like CBT (cognitive-behavioral therapy) [9].

AI's impact isn't limited to patient care — it can also help improve healthcare systems overall. For example, AI-enhanced electronic health records can review a patient's medical history and suggest appropriate treatment options [10]. Moreover, AI-driven self-assessment tools allow individuals to track their mental health and detect possible concerns early on, giving them a greater sense of control over their well-being.

One of the expanding uses of AI in the mental health field is providing online emotional support for young people. AI-powered platforms can offer virtual counselling, helping children and teenagers improve their communication skills, cope with stress, and better manage their emotions [11].

In this study, our aim was to investigate how AI could assist children with neuropsychiatric disorders in enhancing their behavior. To gain deeper insight into the clinical environment these children encounter, we partnered with the Palestine Childhood Institute in Nablus. There, we tested our AI-based solution with children undergoing therapy sessions. This research places particular emphasis on supporting children with neuropsychiatric conditions in Palestine, a region where such disorders are especially common.

To aid therapists, we developed a software application integrated with an interactive toy called "Spark Humanoid." This AI-powered tool is designed to assist pediatric psychologists in their work with children who have behavioral challenges. The system incorporates AI algorithms into gameplay, giving therapists an innovative way to achieve specific therapeutic goals. Our approach uses a convolutional neural network (CNN) [12,13] to analyze children's emotions while they play. This feedback helps specialists track therapeutic progress and assess the child's overall development.

The rest of this paper is structured as follows: Section 2 provides background research and details the system design. Section 3 explores how neural networks are used for emotion recognition and presents the results. Section 4 summarizes our findings.

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2. Methods

2.1 Tech-Enhanced Therapy for Neuropsychiatric Disorders

Over the past five years, there has been a growing integration of various control systems and technologies in the treatment and management of neuropsychiatric disorders. These technologies have become increasingly attractive to therapists as an alternative approach to traditional treatment methods.

For this study, a collaboration was established with a diagnostic and therapeutic center in Nablus, where close interaction with developmental psychiatrists and psychologists provided valuable insights into the therapeutic procedures used for neuropsychiatric conditions. Each interview conducted was meticulously documented in PDF format, capturing only the essential information required for analysis. After a detailed evaluation, key findings were compiled into a comprehensive report, ensuring clear communication with the design team. Therapists emphasized the importance of personalized treatment plans, customized to meet the unique needs of children with neuropsychiatric disorders, given the diverse symptoms these children exhibit.

A crucial aspect of therapy for these children is stimulus control. Children who are constantly seeking sensory input require structured stimulation, while those with attention deficits need predictability to anticipate future events. The ability to personalize therapeutic approaches was identified as a distinct feature of our system, setting it apart from existing interventions and highlighting its potential for significant impact in the field.

During the analysis phase, several key functional requirements were identified:

- Facial expression recognition
- Personalized treatment methodology
- Real-time data collection
- Data processing
- Monitoring treatment progress

The primary goal of this study was to provide therapists with a user-friendly tool that simplifies data collection and analysis, building upon insights from previous research. The study also aimed to introduce an innovative cognitive behavioral therapy (CBT) approach that integrates artificial intelligence (AI). The purpose was to demonstrate how AI can improve the quality of care for children with neurodevelopmental disorders.

As children engage in therapeutic exercises, the system instantly detects and records their facial expressions, capturing their emotional reactions in real time. This information is securely stored on servers, where it is processed and compiled into comprehensive reports. These reports provide therapists with valuable feedback and deeper insights into the child's emotional progress and overall development. The system's architecture is shown in Figure 2.

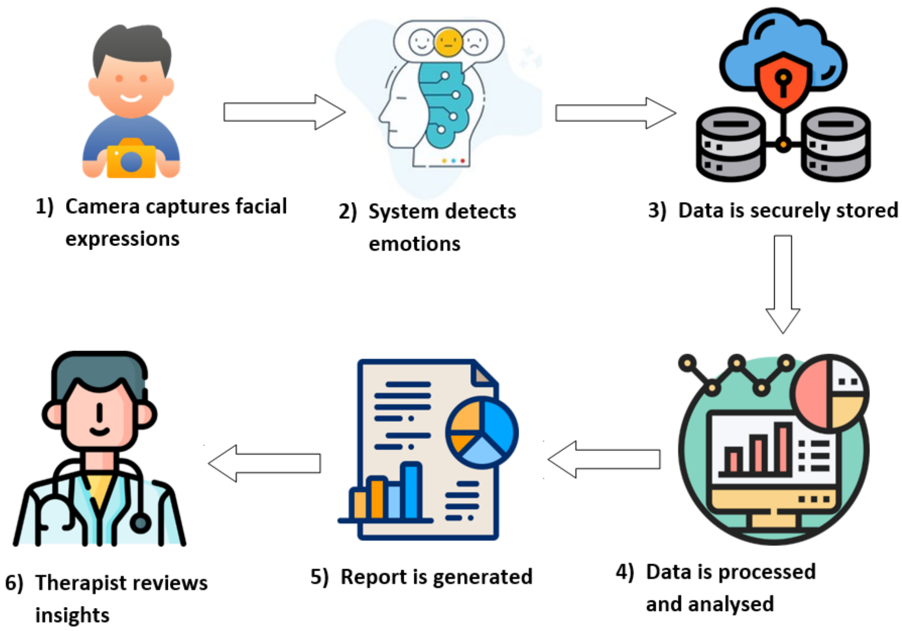

Fig. 2 *System's architecture*

2.2 Interactive Game Using A* Algorithm

To validate the research concept, a series of interactive digital games were developed to replicate traditional paper-based activities for children with psychological and neurological disorders. These digital tools are designed to enhance cognitive awareness, comprehension, and memory retention. Using React, four distinct games were implemented: a matching game, a memory game, a puzzle game, and a pronunciation assistance game.

Inside the game, a specialist's voice guides children in pronouncing words correctly, ensuring an engaging and effective learning experience. These interactive exercises are de-signed for children with psychological and neurological disorders, incorporating sound effects to enhance engagement and participation. The games were developed under the supervision of Dr. Farah Darwa, Program Director and Clinical Psychologist at the Palestinian Child Institute in Nablus, Palestine [14].

The A* algorithm [15] is integrated into the AI system to support children in various activities, including puzzle games. In this context, artificial intelligence helps determine the next step needed to solve the game or complete an exercise.

A* is a search algorithm designed to find the shortest path between an initial and final point. It is widely used in map navigation, efficiently identifying the most direct route. Originally developed for graph traversal and autonomous robot navigation, A* remains one of the diagnosis e most effective pathfinding algorithms. It prioritizes the exploration of shorter paths, making it both optimal and complete. An optimal algorithm guarantees the least costly solution to a problem, while a complete algorithm ensures all possible solutions are explored.

In the case of a sliding puzzle, a common heuristic for the A* algorithm is counting the number of misplaced tiles, providing an estimate of how close the current state is to the solution. Figure 3 shows the pseudocode of the A* algorithm for the puzzle game.

```
function A_Star(start, goal):
    open_set ← {start}
    g[start] ← 0
    f[start] ← g[start] + h(start)

    while open_set is not empty:
        current ← node in open_set with lowest f
        if current == goal:
            return path to current

        remove current from open_set
        for each neighbor of current:
            temp_g ← g[current] + 1
            if neighbor not in g or temp_g < g[neighbor]:
                g[neighbor] ← temp_g
                f[neighbor] ← g[neighbor] + h(neighbor)
                record path from current to neighbor
                add neighbor to open_set

    return failure
```

Fig. 3 *Pseudocode of A* algorithm*

2.3 Emotion Detection Using Convolutional Neural Networks

As the child engages with the game, the application continuously analyzes their facial expressions in real time. Using Convolutional Neural Networks (CNNs), it detects faces and identifies emotional cues, capturing subtle changes in expression. CNNs have proven to be highly effective in emotion classification, particularly in video and image processing tasks. The system then processes this data to recognize patterns, offering valuable insights into the child's emotional responses. These insights help assess the effectiveness of the therapy.

Figure 4 illustrates the key components of the emotion recognition system.

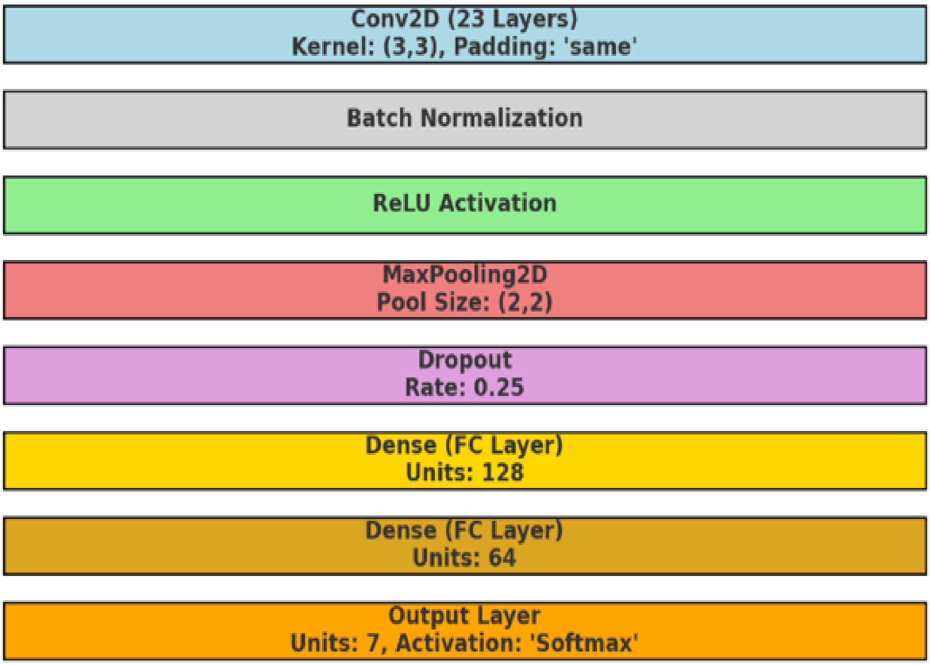

Fig. 4 *Convolutional neural networks (CNN) structure*

3. Results and Discussion

3.1 Dataset

After collecting a sample of 28,821 images [16], the emotional keywords were mapped to create seven broad categories. The images were processed to ensure that faces were nearly centered and occupied a similar amount of space in each image.

Table 1 *Data sample*

Emotion	Number of images
Anger	3993
Disgust	436
Fear	4103
Happy	7164
Sad	4938
Surprise	3205
Neutral	4982

3.1.1 Pre-processing

For face identification, we chose the Multi-task Cascaded Convolutional Network (MTCNN) [17]. MTCNN uses a sequence of three convolutional networks working together to detect faces and locate five key facial landmarks. This process is shown in Figure 5.

3.1.2 Normalization

During both training and testing, we applied a 5×5 normalization filter to the images to adjust pixel intensity levels. This step helped reveal important patterns in the data, making it easier for the model to learn and boosting overall accuracy.

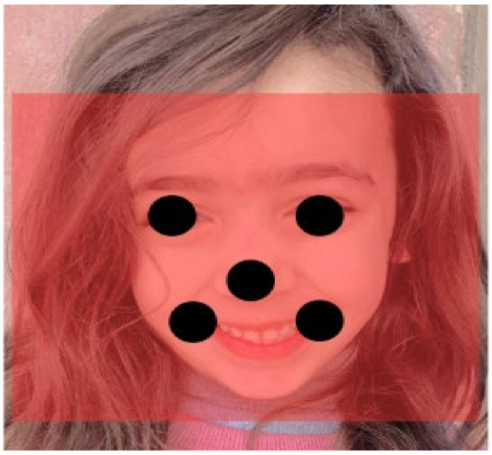

Fig. 5 *MTCNN*

3.2 Model Selection and Evaluation

The CNN model was carefully crafted to suit the specific demands of the classification task. It features several convolutional layers, each paired with batch normalization and dropout layers to help the model generalize better and prevent overfitting. These are followed by fully connected layers, which ultimately lead to a Softmax output layer designed for multi-class classification. Every part of the model was intentionally chosen to boost performance, enhance feature extraction, and strengthen its ability to learn effectively from the training data.

Table 2 offers a detailed breakdown of the model's architecture, outlining the types of layers used, their settings, and the rationale behind each design decision.

Table 2 *Detailed overview of the CNN model's architecture*

Layer/Operation	Description	Number
Conv2D	Filters: Kernel size: (3, 3), Padding: 'same', Input shape: (244, 244, 1)	23 Layer
Batch Normalization	-	-
Activation ('Relu')	-	-
MaxPooling2D	Pool size: (2, 2)	-
Dropout	Rate: 0.25	-
Dense (1st Fully Connected Layer)	Units: 128	-
Dense (2nd Fully Connected Layer)	Units: 64	-
Dense (Output Layer)	Units: number of classes (7), Activation: 'Softmax'	-
Adam Optimizer	Learning rate: 0.001	-

When training a Convolutional Neural Network (CNN), it's important to compile the model first to set key parameters like the loss function, optimizer, and evaluation metrics. This step guides how the model learns and helps measure its performance.

- **Loss Function:** We use categorical cross-entropy as the loss function because it's ideal for classification tasks where the labels belong to distinct categories. This function measures the difference between the predicted probabilities and the actual class labels, helping the model improve its accuracy.
- **Optimizer**: The Adam optimizer (Adaptive Moment Estimation) is chosen for its effectiveness with large, complex datasets. It combines ideas from AdaGrad and RMSProp to adjust the learning rate dynamically, which speeds up training and leads to better overall results.
- **Evaluation Metrics:** Accuracy is used as the primary performance metric, measuring the proportion of correctly classified instances. This provides an intuitive and reliable assessment of the model's effectiveness in distinguishing between different classes.

The results of the model training and evaluation are presented in Table 3.

Table 3 *The results of the model training*

Epoch	Training Loss	Training Accuracy
1	1.041	0.6
2	0.8682	0.6635
3	0.8124	0.688
4	0.7723	0.7038
5	0.7449	0.7174
6	0.7214	0.7219
7	0.7032	0.7298
8	0.6869	0.7385
9	0.6725	0.7431
10	0.6574	0.7483
11	0.666	0.7388
12	0.7307	0.725
13	0.7423	0.7571
14	0.7236	0.7536
15	0.6177	0.8107
16	0.7033	0.7464
17	0.6053	0.7964
18	0.5815	0.7964
19	0.5464	0.8286
20	0.4932	0.8286
21	0.4599	0.8268
22	0.3758	0.8628
23	0.3028	0.8949
24	0.2456	0.9179
25	0.2467	0.913

The training results show steady improvement, with accuracy increasing from 60% (epoch 1) to 91.3% (epoch 25) and loss decreasing from 1.041 to 0.2467, indicating strong model convergence and effective learning. The model was tested on a real dataset, achieving an accuracy of 90%. Below is a screenshot of two sample results, as shown in Figure 6.

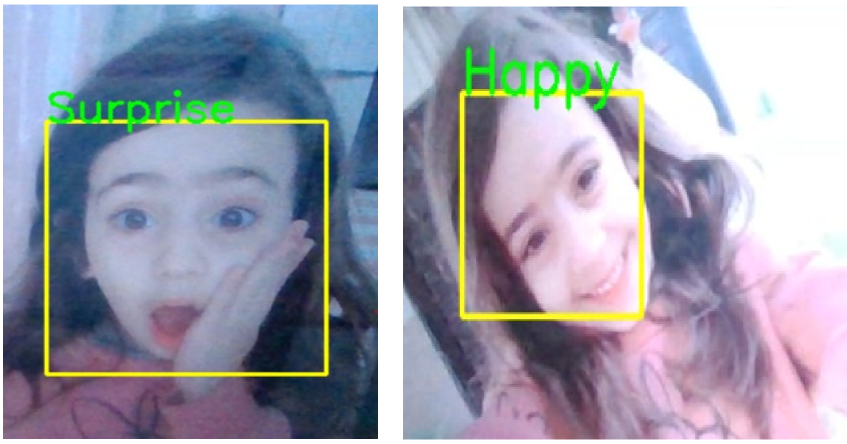

Fig. 6 *Emotion recognition on test dataset – sample output*

3.3 Comparative Analysis

In May 2023, the Palestinian Institute for Childhood conducted a series of experiments to explore how children interacted with the Spark system. These experiments took place over two sessions.

In the first session, the children were introduced to the Spark processor and given instructions on how to use the control system. They quickly adapted to it, showing enthusiasm and a high level of cooperation.

During the second session, the children participated in a puzzle activity, first using a 9×9 paper sheet. Researchers observed how they interacted with the paper surface and measured the time taken to complete the task. They then attempted the same puzzle on Spark, a digital platform, with their completion times recorded for comparison. In addition to puzzles, the session included exercises focusing on memory retention, matching, and writing numbers and letters.

Interestingly, the children demonstrated better pen-holding skills and overall engagement when using the digital platform compared to the traditional paper method. Their approaches varied some started with paper before transitioning to Spark, while others began with Spark before moving to paper.

Table 4 presents the time taken to solve different types of puzzles, categorized according to the children's stage of disorder. The first recorded time corresponds to the paper-based puzzle, while the second reflects the digital version on Spark. Notably, the children took longer, appeared more distracted, and showed signs of boredom during the paper-based activity. In contrast, they were more engaged, active, and happier while using the robotic control system.

Table 4 *Time it takes the children to complete the tasks on paper versus Spark*

Task	Theoretical	With Spark
Puzzle task 9*9	25:69	12:34
Memory Task	50:59	33:28
matching	39:28	37:98
writing numbers	55	41
Puzzle task 2*2	50	60

As the children worked on their tasks, a special beam was activated to capture their emotions in real time. This feedback helped assess their performance, as shown in Figure 7. For their writing exercises, they were asked to choose a number between 0 and 3. Their reactions ranged from happy to neutral. However, when they reached number 4, which represented a higher level of difficulty, their expressions shifted to surprise and even fear as they faced the challenge. All the collected feedback was compiled into a report and shared with therapists at the Palestine Childhood Center.

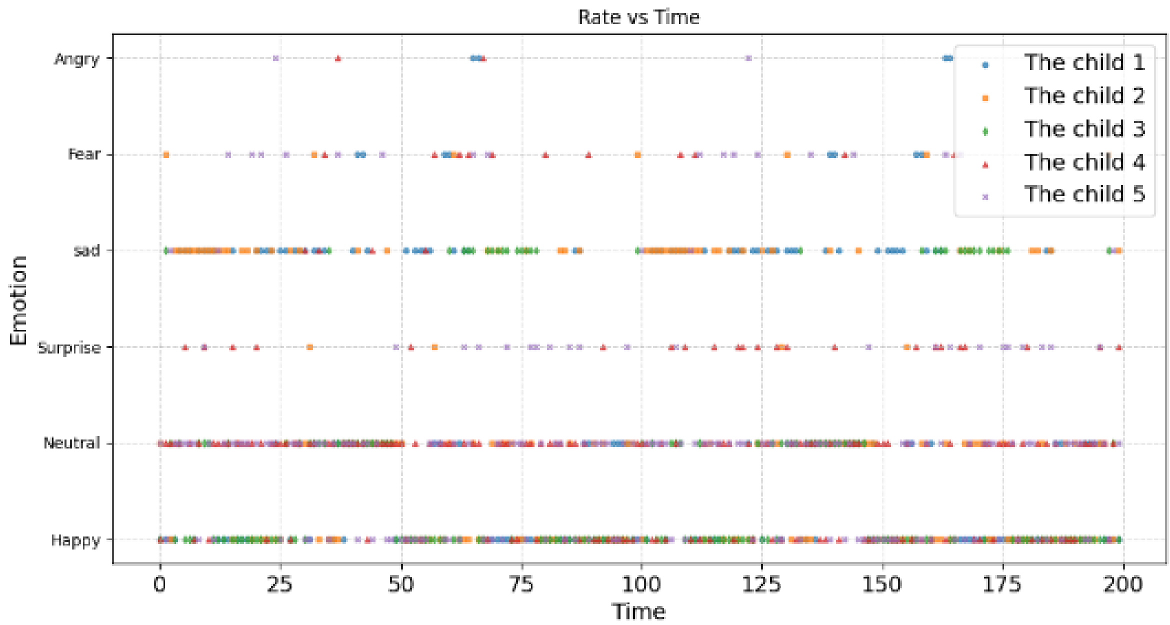

Fig. 7 *Students face emotional output from the task with Spark*

As shown in Figure 7, the feedback provided to specialists helps them assess children's performance while using Spark. In the chart, the Y-axis represents the children's emotions, while the X-axis represents time. The system captures emotional responses every 100 milliseconds, allowing specialists to evaluate how children feel during each task and monitor their progress over time.

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The results indicate that most emotional responses fell under the "happy" and "neutral" categories, suggesting that children responded positively to Spark. They appeared more comfortable and engaged compared to traditional paper-based tasks, where their emotions were predominantly categorized as "sad." However, there was still a small percentage of "sad" expressions, which is expected given the nature of neuropsychiatric disorders and the challenges these children face during structured activities.

To further explore the adoption of AI in therapy, we conducted a survey at the Palestinian Childhood Center to gauge staff attitudes toward integrating AI into treatment. The results were largely positive, with 90% of participants expressing a strong interest in using AI applications in therapy sessions.

The survey, based on the Unified Theory of Acceptance and Use of Technology (UTAUT) [18-21], examined four key factors influencing AI adoption. The first was performance expectations, where 49% agreed and 30% strongly agreed that AI could help continuously evaluate both therapists and patients. The second factor was ease of use, with 40% believing AI applications would be clear and easy to interact with. The third dimension focused on social influence, recognizing how professional communities shape attitudes toward technology adoption.

Finally, the survey assessed available resources, revealing a major challenge 70% of respondents felt that the necessary tools to implement AI-based therapy were not currently available.

This study emphasizes the importance of closing existing gaps by ensuring the proper infrastructure and training are in place for AI-powered therapy. Tackling these challenges will enable institutions to more successfully implement AI technologies, leading to better therapeutic results for children with neuropsychiatric conditions.

4. Conclusion

This study shows that AI can be a helpful part of therapy for kids with emotional and social challenges. We built a system called Spark Humanoid that uses AI to play interactive games and recognize emotions. It helps therapists connect more easily with children who find social interaction and expressing feelings hard. While working with the Palestine Childhood Institute, we saw that kids were more focused and open during sessions when AI was involved. They shared their feelings better and interacted more with others. The AI isn't here to replace therapists, but it can support them by giving useful insights and helping make therapy more engaging. There's still work to do to improve the system and make it easier to use in everyday therapy. But with care and the right approach, AI can help give children more personal and meaningful support as they grow and learn.

Acknowledgement

The authors would like to thank An-Najah National University for its support.

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *M.A., E.N.;* ***data collection:*** *M.A., E.N.;* ***analysis and interpretation of results:*** *M.A., E.N.;* ***draft manuscript preparation:*** *M.A., E.N. All authors reviewed the results and approved the final version of the manuscript.*

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